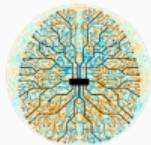


# Machine Learning for Radiometer Calibration

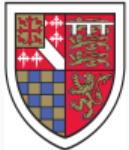
Samuel Alan Kossoff Leeney

2nd Year PhD Candidate

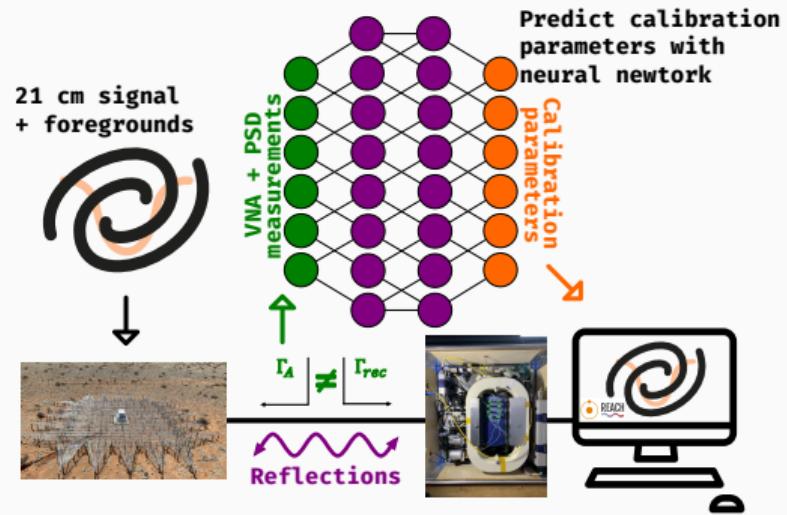
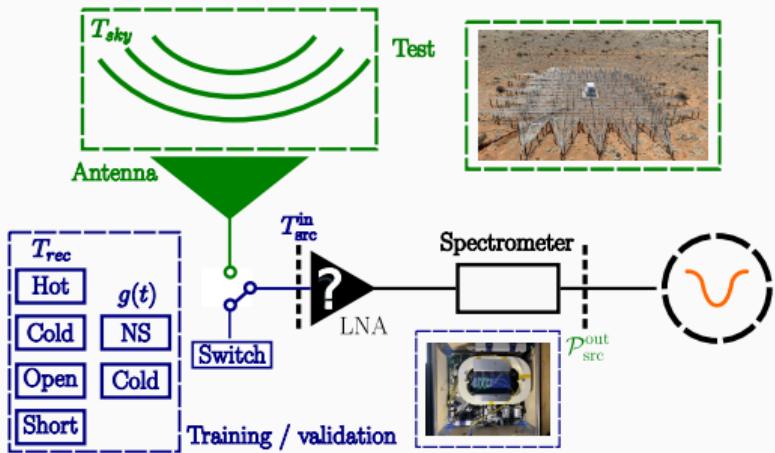
With: Harry Bevins, Eloy de Lera Acedo, Will Handley, Rohan Patel, Kaan Artuc, Jiacong Zhu



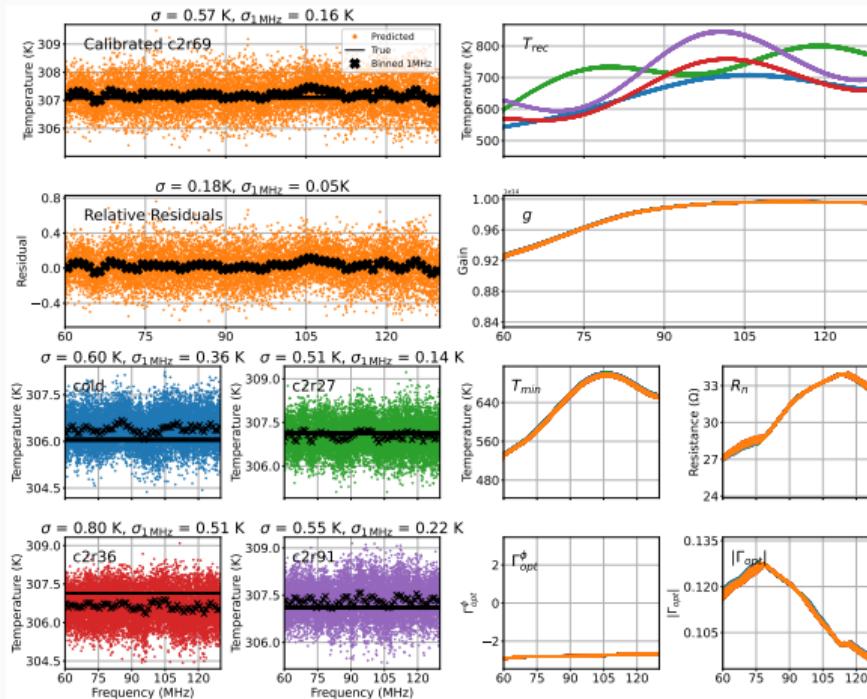
UNIVERSITY OF  
CAMBRIDGE



# ML calibration overview

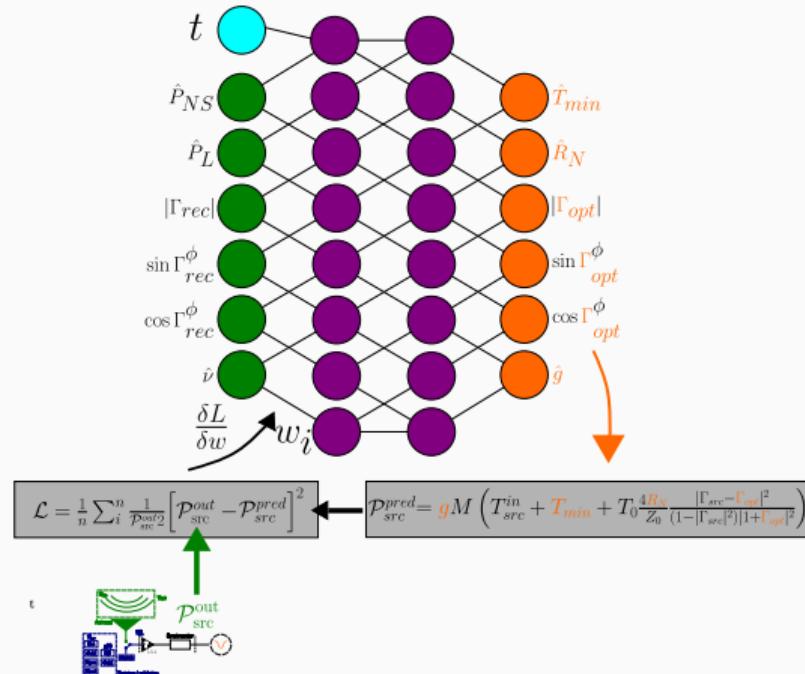


# Testing on internal validation source

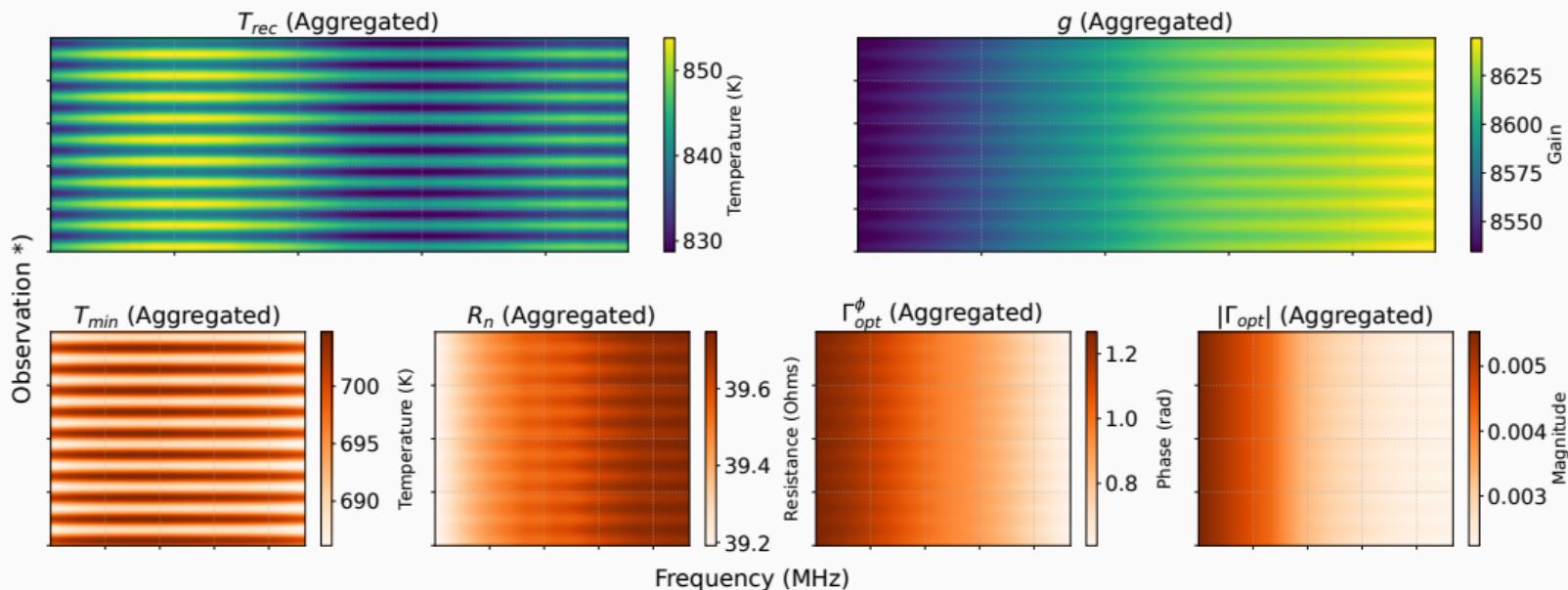


**Figure 1:** Temperature calibration using internal sources on the REACH receiver

# Neural Network Time Evolution

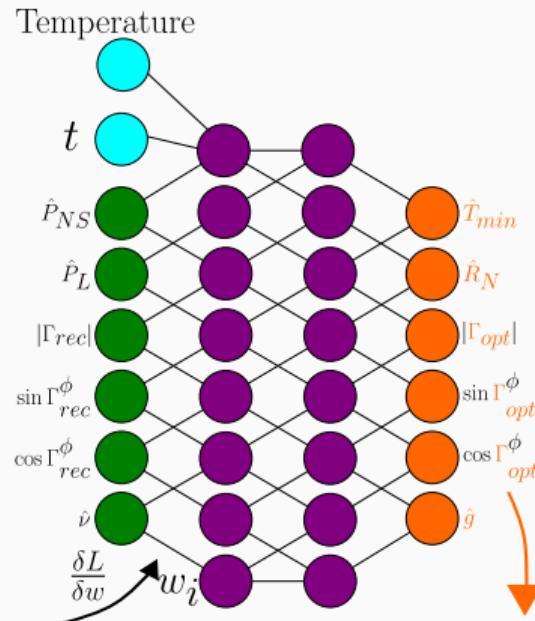


## Inject system drift



Inject a time varying sinusoid into  $T_{min}$  and predict the noise parameters → the network recovers this 'system drift'

# Modeling environmental features



We can train on features that cannot be modeled analytically

$$\mathcal{L} = \frac{1}{n} \sum_i^n \frac{1}{\mathcal{P}_{src}^{out2}} \left[ \mathcal{P}_{src}^{out} - \mathcal{P}_{src}^{pred} \right]^2 \quad \leftarrow \quad \mathcal{P}_{src}^{pred} = gM \left( T_{src}^{in} + T_{min} + T_0 \frac{4R_N}{Z_0} \frac{|\Gamma_{src} - \Gamma_{opt}|^2}{(1 - |\Gamma_{src}|^2)(1 + |\Gamma_{opt}|^2)} \right)$$



## Conclusions

### Component Modelling

Learn the effect of complex internal components such as switches, cables, etc

### Temporal Dynamics

Learn time dependant system behaviour

### Extended Inputs

Train on non-standard inputs, such as box temperature